Development and Evaluation of an Algorithm for Objective Bias Correction of Dynamical Forecasts at Different Scales

A Synopsis of the Thesis to be submitted to the

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1. Title

Development and Evaluation of an Algorithm for Objective Bias Correction of Dynamical Forecasts at Different Scales.

2. Summary of the Thesis

2.1 Background

The atmospheric systems are characterized by complex multi-scale interactions; the resulting nonlinearities make forecasting of atmospheric variables a major scientific challenge. At the same time, many applications, from weather forecasts to agro-advisories to disaster management, require meteorological forecasts at various scales. In spite of their many limitations, dynamical models have emerged as the most versatile tools for generating forecasts at different spatial and temporal scales (Holton 2004; Wallace and Hobbs 2006). Although significant progress has been made in terms of model physics as well as numerics in recent years, the skill of dynamical models is still limited in many aspects (Dee 2005; Rodwell and Palmer 2007). The identification of the model discrepancy and ability is crucial while selecting the dynamical models for the purpose of weather and climate prediction and for further improvements in model physics and configurations (Kalnay 2003; Palmer and Hagedorn 2006; Swanson and Roebber 2008; Nicolis et al. 2009). The characterization of the forecast errors and its sensitivity to the choice of different physical parameterizations provides greater confidence in the model outputs and qualifies its application for predicting the real time events (Pielke, 2002). This can be achieved by rigorous validation and sensitivity studies of the simulations carried out by these models for various synoptic conditions and initialization datasets (Kalnay 2003; Frehlich and Kelley 2008; Frehlich 2011).

A major difficulty in addressing model systematic error (or bias) is that it may originate from a number of sources, such as model numerics, model physics as well as forecast methodology (Mass et all. 2002, 2003; Wu et al. 2005; Dee 2005; Monache et al. 2006; Gel 2007; Judd et al. 2008; Houtekamer et al. 2009; Bao et al. 2010; Goswami et al. 2011). As the bias due to numerics and forecast methodology may primarily arise from

the projection of model data on a given horizontal and vertical grid to point observation, this part of the bias may be expected to be somewhat systematic in nature (Steed and Mass 2004; Abramowitz et al. 2007; Mass et al. 2008). In particular, this bias primarily arises from an adopted grid and methodology for interpolation. Identification of this bias of a given model and its removal through an objective method can significantly improve forecast skill (Stewart and Reagan-Cirincione 1991; Schubert and Chang 1996). However, the efficiency of the removal of such bias depends strongly on the algorithm used. Further, while an algorithm may be universal in its potential application, it needs to be calibrated and validated for certain regions. Similarly, the algorithm may also change based on the physics and the dynamics of the system.

2.2 Objective and Scope of work

The thesis describes development of new algorithms for objective bias correction of model simulations for achieving enhanced and significant skill in advance forecasting. While the focus is on the Indian region, we consider a number of spatial and temporal scales, from station scale to tropical cyclone, and from daily to monthly forecasts. Similarly, we consider more than one dynamical model to evaluate our method. The evaluation and validation encompass both comparison against actual observations and relative performance with respect to other methods as well as null hypotheses. Chapter-wise outline of the thesis is provided below.

Chapter-1 Introduction

This chapter begins with a brief description of the atmospheric system and their dynamics, Numerical Weather Prediction (NWP), different types of NWP model error and the sources of these errors in dynamical forecasts. The major contributions by earlier researchers on different bias correction methods are briefly described. This chapter also deals with the basic principle objective non-linear bias correction method in the model simulation with respect to observations. Finally, the chapter describes the objective of the study.

Chapter-2 Objective Bias correction with GCM Forecasts: Tropical Cyclone

A brief description of the tropical cyclone over the north Indian Ocean basins, events and data used are described. Different objective bias correction algorithms used to improve forecast skill of intensity, track and cyclogenesis are also outlined in this chapter. The intensity and location forecasts are generated using an optimized configuration of a variable resolution Global Circulation Model (VR-GCM) that combines the advantages of a limited area model and a global circulation model (version LMDZ3 developed at LMD, France). Results on intensity and location forecasts with enhanced reliability from raw forecasts from VR-GCM using objective non-linear debiasing are presented.

Chapter-3 Objective Bias correction: Station-Scale Forecasts from LAM

While meso-scale models today can support horizontal grid spacing down to a few kilometers or less, downscaling of model forecast to arrive at station scale values will remain a necessary step for many applications. This chapter gives the details of the bias correction algorithm developed in this research for station-scale forecasts of temperature using Pennsylvania State University/National Center for Atmospheric Research (PSU/NCAR) meso-scale model version 3 (MM5) over the Indian region. For station-scale forecast, it is shown that the skill of the debiasing forecast is significant against raw forecasts. This chapter also provides a comparison of the present method with similar methods.

Chapter-4 Objective Bias Correction: Meso-scale Forecasts.

Meso-scale forecasts are important for many applications, especially for high-impact weather over urban locations; the complexity and the variability of the flow due to structures and anthropogenic activities of a mega city pose new challenges to meso-scale forecasting. This chapter describes the source of observation, structure of meso-scale observation and bias correction algorithm for temperature of different session. In this study we consider four stations located in and around Delhi separated by aerial distance of a few kilometers. It is shown that for all the four locations the skill of the

debiased forecast is significant against the zero skill of raw forecasts and significantly higher than that of a 7-day running mean error removal (null hypothesis).

Chapter-5 Objective Bias correction: Station-Scale Analysis from Reanalysis

Reanalysis data like those from National Center for Environmental Prediction (NCEP), provide a versatile, and sometimes only, long-term, multi-variable data at a location. However, Reanalysis data is known to contain significant biases that depend on geographical location. This chapter describes impact of the bias correction algorithm applied to NCEP Reanalysis for multiple locations over India. It is shown that objective bias correction can effectively improve quality of such analysis at station-scale.

Chapter-6: Conclusions and Future Directions.

This chapter includes a summary of the entire study and the major findings, and discusses some of the limitations. Finally the chapter points towards some future directions for potential improvements.

3. Objective Non-linear Debiasing:

Removal of systematic parts of error (or bias) through an objective bias correction (referred to as debiasing) procedure can significantly improve forecast skill (Stewart and Reagan-Cirincione 1991; Goswami and Mallick 2011). The bias in the raw forecasts was found to be dependent on the value of the forecast. The generic methodology of objective non-linear debiasing adopted in this thesis is to determine debiasing parameters based on a training set and then apply the method with these parameters on a test set.

We consider a debiasing algorithm as

$$\mathbf{X}_D = \mathbf{X}_R [1 + \alpha - \beta * \mathbf{X}_R] \qquad (1)$$

Where $\mathbf{X}_D$ is the debiased forecast, $\mathbf{X}_R$ is the raw forecast. The optimum values of α and β were obtained through a search procedure to minimize $|X_F - X_O|$ where X_F and X_O

represent, respectively, the forecast and the observed values. In this procedure a range of values of α and β are considered with sufficiently small intervals to arrive at the optimum values characterized by the lowest $|X_F - X_O|$ for the training sample.

Two different types of objective nonlinear debiasing have been considered in this thesis. First, optimum values of debiasing parameters were obtained using the total number of forecasts. As this procedure (referred to as potential debiasing; DFP) uses in-sample data, the skill assessed is not strictly realizable, and we shall refer to the skill as potential skill. The skill with potential debiasing essentially is indicative of maximum skill attainable with the procedure, or enhancement in skill likely if larger training samples were available. The optimum values of debiasing parameters are obtained by using a search procedure for minimum average error for the training set. The search algorithm begins with initial values of debiasing parameters (generally from large negative values) and allows small increments at each step until final (generally large positive values) values are reached; the pair with minimum error is adopted. Secondly, for a more realistic assessment of (realizable; DFR) skill through non-linear debiasing we have next applied the debiasing algorithm to a training set to determine the debiasing parameters; these debiasing parameters are then applied outside the training set, for cross-validation of debiasing parameters (Wilks 2006; Hamill et al. 2008). Different size of training set has been considered for different study of bias correction like station scale forecast, tropical cyclone intensity, location forecasts and meso-scale forecasts.

4. Tropical Cyclone Forecasts

With increasing socio-economic activities in coastal areas the world over, the damage potential of tropical cyclones has considerably increased. While there has been significant progress in modeling and forecasting of cyclones over the past decades, there is also growing expectation and demand for longer range and higher accuracy (Anderson 1996; AMS council 2000). Apart from the storm surge, the damage potential of a tropical cyclone is primarily determined by the strength (intensity) of the wind,

either in terms of direct damage or induced storm surge. In particular, the peak intensity of a storm is a measure of its maximum damage potential (Emanuel 1987, 1988, 1995). Thus an accurate and advance prediction of the peak intensity is a critical input for efficient and pro-active disaster management. One factor that limits skill of the numerical models is the bias in the model forecasts with respect to observations. This study shows that a non-linear objective debiasing can generate intensity and location forecasts with enhanced reliability from raw forecasts. The forecast for thirty-six cases of storms and cyclones over north Indian Ocean during 1990-2009, are generated using an optimized configuration of a variable resolution Global Circulation Model (VR-GCM) that combines the advantages of a limited area model and a global model; version LMDZ3 developed at LMD, France (Sadourny and Laval 1984; Sharma and Sadourny 1987; Sabre et al. 2000; Goswami and Gouda 2009, 2010). The hindcasts were carried out in a completely operational setting, that is, without assuming any observed information beyond the day of the initial condition.

Table 1. Analysis of Skill Score, Average Absolute Error and Average Bias for raw, non-linear potential, nonlinear realizable and climatological forecasts.

Forecast	**Skill Score**	**Average Absolute Error (m s^{-1})**	**Average Bias (m s^{-1})**
Raw	0.01	11.6	-9.86
Non-linear Potential	0.75	5.10	0.58
Non-linear Realizable	0.65	6.30	0.67
Climatological	0.00	12.9	0.003

A scrutiny of skill scores, average absolute error (m s^{-1}) and average bias for different type of intensity forecasts of tropical cyclone (Table 1) shows that while raw forecast and

the climatological forecasts have very low or *zero* skill score, the non-linearly debiased forecasts have appreciable skill score. In terms of average absolute error, both potential and realizable skill of the non-linear debiasing forecast has only 5.1 m s^{-1} and 6.3 m s^{-1}, compared to raw forecast and the climatological forecast (11.6 m s^{-1} and 12.9 m s^{-1}).

We have combined an objective debiasing to improve skill of intensity and location forecast of cyclones over the north Indian Ocean. Objective non-linear debiasing not only improves forecast skill above raw forecast, but the skill score is appreciable in general. The consistent performance of the model for different conditions makes it an attractive tool for tropical cyclone forecasting. In an actual application one could generate multiple forecasts, each for an ocean basin, with a grid that has been critically evaluated for the basin

While there are few studies on intensity and track forecast for cyclones over the north Indian Ocean, there have been several methods and studies on intensity and track forecast over the Atlantic and Pacific (DeMaria and Kaplan 1999; Knaff et al. 2003, 2005; Blackerby 2005; DeMaria et al. 2007). The National Hurricane Centre (USA) has documented skill (NHC Report 2008) in forecasting of track and intensity for cyclones over the Pacific and the Atlantic from a number of models for leads 12-72 hours (NHC Report 2008).

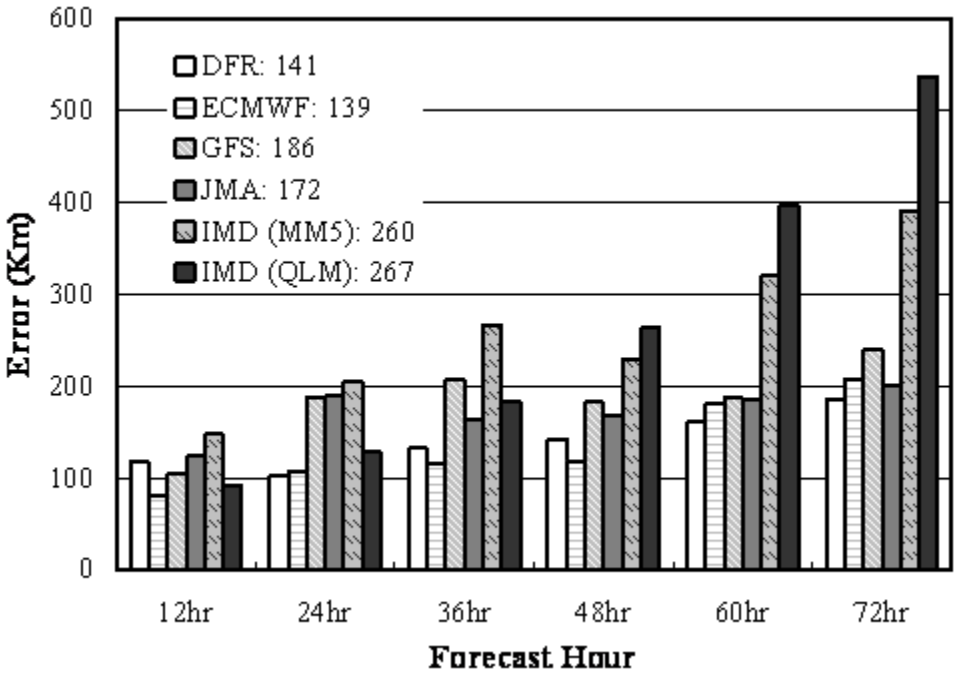

Figure 1 A comparison in terms of average absolute error (Km) for debiased forecasts (DFR) with the standard error from various operational agencies; European Centre for Medium-Range Weather Forecasts (ECMWF), Global Forecasting System (GFS) , Japan Meteorological Agency (JMA) and India Meteorological Department (IMD) at different forecast hour. The numbers in the panel respectively represents the averaged forecasts error (Km) up to 72-hour for the corresponding case (Kotal et al. 2009, Roy Bhowmik and Durai 2010).

A comparison of track forecast in terms of average absolute error (Km) for debiasing forecasts (DFR) with the standard error from various operational agencies, like European Centre for Medium-Range Weather Forecasts (ECMWF), Global Forecasting System (GFS), Japan Meteorological Agency (JMA), India Meteorological Society (IMD) at different forecast hour (Figure 1) [For TC track prediction, IMD operationally runs three regional models, Limited Area Model (LAM), fifth-generation Pennsylvania State University-National Center for Atmospheric Research Mesoscale Model (MM5) and Quasi-Lagrangian Model (QLM) for short-range prediction]. For 12-hour forecast, the debiased forecasts are less skillful then ECMWF, GFS and IMD-QLM forecasts, but have greater skill than those of JMA and IMD-MM5 (Kotal et al. 2009, Roy Bhowmik and Durai 2010). The 24-hour DFR forecasts are superior to all the other except ECMWF for

which the skill is comparable. At other forecast hours, the DFR forecast have generally better skill. In particular, the average error over the 12 to 72 hour forecasts is the lowest for DFR. It is also interesting to note that growth of error for DFR is the lowest and is essentially constant as against rapid growth of error for the other forecasts.

Table 2. A comparison of performance of non-linear debiasing potential skill (DFP) and realizable skill (DFR) with current intensity forecast by different methods.

Performance (% of cases)	Percentage (%) of cases							
	DFP	**DFR**	**SHF5**	**SHIPS**	**DSHIPS**	**GFDI**	**GFNI**	**NHC**
Under warning $U_P - U_O < -5$ m s^{-1}	10	17	8	5	6	22	27	16
Over warning $U_P - U_O > 5$ m s^{-1}	27	27	27	30	25	19	20	14

A comparison of skill in terms of under warning and over warning of the non-linear debiasing with six other methods including SHIPS, DSHIPS and NHC (Blackerby 2005; Boothe et al. 2006) shows the skill of the presented method to be comparable in some cases but not superior; in general, a distinct pattern does not emerge (Table 2). It should be emphasized, however, that a comparison of skill over north Indian Ocean with that over the Atlantic or the Pacific is not strictly valid as the tropical cyclones over these basins have quite different characteristics. Thus a more robust comparative evaluation of skill would require other methods of intensity forecasts applied to the north Indian Ocean basin. Further, the lead of the forecast in the present case is often more than 72 hours that is used in calculating skill for the other methods.

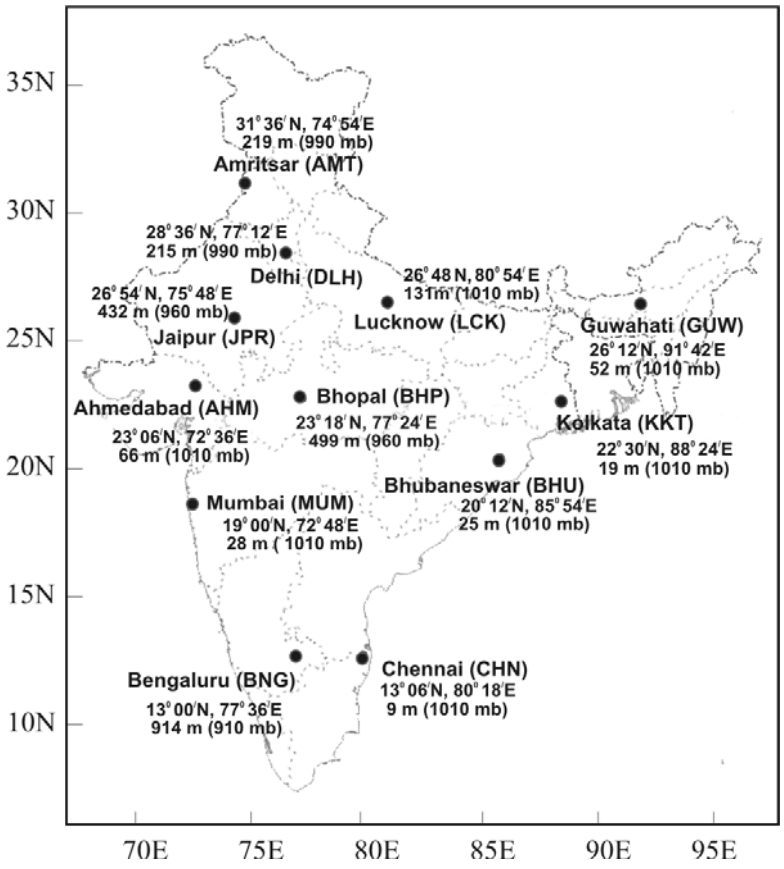

Figure 2 The 12 locations over India considered in this study for objective debiasing. The latitude (^{0}), longitude (^{0}), altitude (m) and pressure level (mb) of each station are mentioned along with the station name. The abbreviation used for station name is given in bracket.

5. Station-Scale Forecasts from Limited Area Model (LAM)

Station-scale forecasts are necessary for many applications related to health (such as vector borne disease), agriculture (such as germination potential) and industry (such as power requirements), where the diurnal cycle of temperature plays a critical role. Such station-scale forecasts from dynamical models have to be necessarily obtained through a procedure of downscaling. Similarly, while typical climate simulations generate fields averaged over thousands of square kilometers, many applications require meteorological filed at local scale. The meso-scale models today can support horizontal grid spacing

down to a few kilometers or less, downscaling of model forecasts to arrive at station scale values will remain a necessary step for many applications.

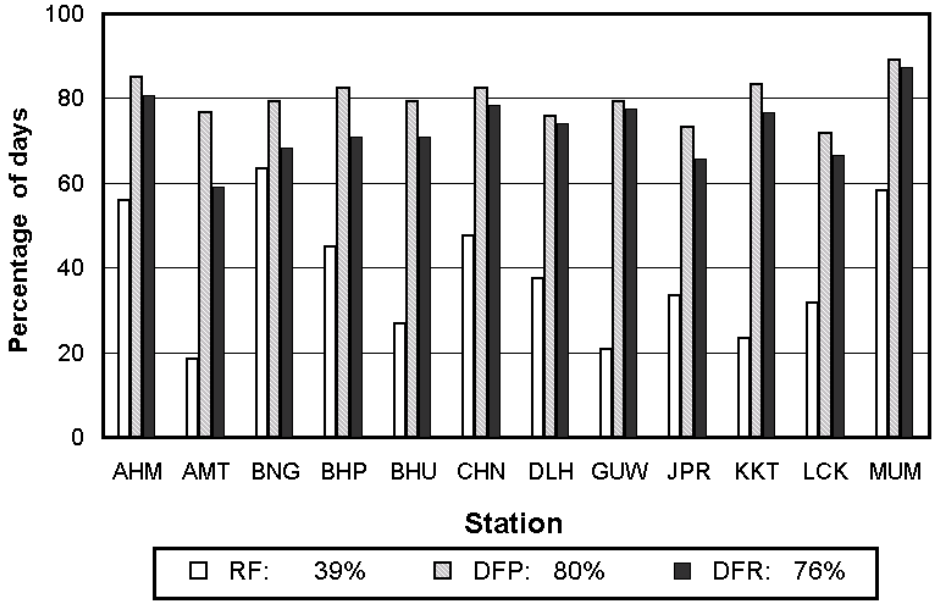

Figure 3 Percentage of days (out of 123 days for RF and DFP, 83 days for DFR) for which daily averaged temperature is in the error bin -1 to 1 ^{0}C from May to August 2009 for each station. The average of all station is given with the legends. The observed station temperatures are adopted from IMD observations, while the station forecasts are downscaled from model forecasts at 10 km resolution.

While generic improvement in model skill requires parallel and comprehensive development in model and other forecast methodology, one way of achieving skill in station scale forecasts without (effort-intensive) calibration of model is to implement an objective bias correction (referred to as debiasing). We show that a non-linear objective debiasing can transform zero-skill forecasts from a meso-scale model (MM5; Dudhia 1993; Dudhia et al. 2004) to forecasts with significant skill. We consider 12 locations over India (Figure 2) representing urban sites in different geographical conditions during May-August, 2009. The model MM5 was integrated for 24 hours with initial conditions from [global gridded analysis (FNL)] of the National Centers for Environmental Prediction Global Forecast System (Final) for each of the days of May-August 2009 in a

completely operational setting (without assuming any observed information on dynamics beyond the time of the initial condition).

Table 3. A comparison of the performance of raw forecast (MM5-RF) and debiased forecast (MM5-DFR) in terms of Mean Absolute Error (MAE), Bias Error (BE) and Root Mean Square Error (RMSE) in maximum (T_{max}) and minimum (T_{min}) temperature by different methods. For MM5-RF and MM5-DFR all parameters are calculated out of 123 days and 83 days respectively from May to August, 2009.

Model	**MAE (^{0}C)**	**BE (^{0}C)**	**MAE (%) < 1^0**	**RMSE in T_{max} (^{0}C)**	**RMSE in T_{min} (^{0}C)**
ETA *	2.6	0.9	26	—	—
ETAKF *	1.9	0.0	37	—	—
ETA7DBR*	1.8	0.0	37	—	—
ETAMOS *	1.5	0.1	42	—	—
MM5-RF$^+$	3.2	-0.7	39	2.0	1.9
MM5-DFR$^+$	1.1	0.1	76	1.0	0.9
GCM (NCMRWF)†	—	—	—	2.2	1.4

* June – August, 2004 (Cheng and Steenburgh, 2007),

+ May – August, 2009; average over 12 stations, (Present method)

† June – September, 1997-2000; average over 12 stations (Maini et al. 2003).

A summary of skill averaged over the 12 stations for each of the four months shows raw forecasts to have essentially zero or *negative* skill score in all cases. The realizable skill (DFR), while generally lower than potential skill (DFP) as expected, is significant for all the four months. The average errors in daily average temperature, minimum and maximum daily temperatures are generally less than 1 ^{0}C for both DFP and DFR. In terms of percentage of days for which the daily average error is between -1 ^{0}C to +1 ^{0}C, the debiased forecasts appear to be far superior to raw forecasts for all the months; while nearly 76% (80%) of days for DFR (DFP) lie within -1 ^{0}C to +1 ^{0}C when averaged over

all the for months, the corresponding percentage for raw forecast is only 39% (Figure 3). A comparison of skill of the present method with a number of other methods [like the Eta Model (ETA) which was renamed the North American Meso (NAM) model in 2005, model output statistics with ETA model (ETAMOS), the Kalman filter with ETA model (ETAKF) and a 7-day running mean bias removal with ETA model (ETA7DBR)] (Maini et al. 2003, Cheng and Steenburgh 2007) for debiasing shows (Table 3) the present method to have generally better skill.

6. Conclusions and Future Directions.

The atmospheric systems are governed by non-linear multi-scale dynamics with interacting scales. The non-linearity as well feedback among various components and the scales pose a serious challenge in predicting these systems with sufficient accuracy; worldwide, improvement of forecast skill of systems like cyclone and extreme rainfall events remains a challenge.

The focus of the thesis has been on improved skill in forecasting through objective bias correction. The basic principle of objective bias correction has been applied to a number of different systems of different scales. On one hand, we have examined forecasting of cyclone track and intensity using a variable-resolution Global Circulation Model; on the other hand, we have considered short-range forecast of diurnal cycles of temperature using a meso-scale atmospheric model. Objective non-linear debiasing not only improves the forecast skill above raw forecast, but results in high skill score in each case.

The consistent performance of the model for different conditions makes it an attractive tool for tropical cyclone forecasting. In an actual application one could generate multiple forecasts, each for an ocean basin, with a grid that has been critically evaluated for the basin. Similarly, the method can be validated for other ocean basins (like Pacific and Atlantic Ocean basins). While we have used a VR-GCM in the present study based on certain considerations, the method presented is quite generic, and can be applied to forecasts from other models, say from high-resolution limited area models, with necessary calibration and validation.

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8. List of Publication

1. Prashant Goswami, **Swapan Mallick**, 2011 “Objective Bias Correction for improved skill in forecasting diurnal cycles of temperature over multiple locations: The summer case.” 26 (1), 26-43, 2011 Journal: *Weather and Forecasting* (American Meteorological Society). doi: 10.1175/2010WAF2222407.1

2. Prashant Goswami, **Swapan Mallick** and K.C. Gouda, 2011 “Objective debiasing for Improve Forecasting of Tropical Cyclone Intensity with a Global Circulation Model”. 2011 Journal: *Monthly Weather Review* (American Meteorological Society), doi: 10.1175/2011MWR3600.1

3. Prashant Goswami and **Swapan Mallick**, “Non-linear Bias Correction for Improved Track Forecasting of Tropical Cyclone” Journal: *Monthly Weather Review* (American Meteorological Society), under advance revision.

4. Prashant Goswami, **Swapan Mallick** and G.K. Patra, “Objective Bias Correction for improved skill in forecasting meso-scale structure over urban location: A Case Study” Journal: *Weather and Forecasting* (American Meteorological Society), under revision.

9. Seminar/ Training /Workshop attended:

1. Participated in "*Intensive Course on Inverse Modelling*" organized by CSIR Centre for Mathematical Modelling and Computer Simulation, Bangalore, June 19-July 27, 2006

2. Participated in the national workshop on "*Dynamics and Simulation of Extreme Events*" at N.A.L, Bangalore during 15th to 17th March 2006. Sponsored by DST, India.

3. Participated in the national workshop on "*Monsoon Forecasting*" at CSIR C-MMACS, Bangalore during February 12-13, 2007. Sponsored by DST, India.

4. Participated in "*96th Indian Science Congress*" held in NEHU, Shillong during 3rd to 7th January 2009.

5. Presented seminar on "*Four Dimensional Variational Data Assimilation with Global Circulation Model*" in National Brian storm meeting organized by Ministry of Earth Science (MoES). India during 19rd to 21th February 2009.

6. Presented seminar on "*Variational Data Assimilation*" in Indian Air Force meeting held in CSIR C-MMACS, Bangalore. March 2009.

7. Presented seminar on "*Four Dimensional Variational Assimilation*" in NDMA meeting held in CSIR C-MMACS, Bangalore. April 2009.

8. Participated in the national workshop on "*Advance Application and Mathematical modeling (AAMM)*" at National Aerospace Laboratory, Bangalore, organized by Council of Scientific and Industrial Research (CSIR) India, during May 23-25, 2009.

9. Participated in the national workshop on "*Data Assimilation course on Global Models*" at NCMRWF, New Delhi, India, during 23rd November to 27th November 2009.

10. Prashant Goswami and Swapan Mallick 2009 "Design of Flight Path for Tropical Cyclone Observation over Bay of Bengal", National conference on "*Second India Disaster Management Congress*"
[Available online at http://www.nidm.gov.in/idmc2/session_cyclone.asp]

11. Presented seminar on "*Validation of Algorithm for Objective Debiasing over India*" in a task force meeting on 'Integrated Analysis for Impact, Mitigation and Sustainability Development' held in 26th October 2010 at CSIR C-MMACS, Bangalore-37.

12. Participated in the national workshop on "*Advance Application and Mathematical modeling (AAMM)*" at National Aerospace Laboratory, Bangalore, organized by Council of Scientific and Industrial Research (CSIR) India, during May 23-25, 2009.

13. Participated in the national workshop on "*Data Assimilation course on Global Models*" at NCMRWF, New Delhi, India, during 23rd November to 27th November 2009.

14. Presented seminar on "*Validation of Algorithm for Objective Debiasing over India*" in a task force meeting on "Integrated Analysis for Impact, Mitigation and Sustainability Development' held in 26th October 2010 at CSIR C-MMACS, Bangalore-37.

15. Presented seminar on "*Improved forecasting skill of track and Intensity forecasting of Tropical Cyclone over North Indian Ocean*" on 3rd March 2011 at CSIR C-MMACS, Bangalore-37.

Signature of the Candidate Signature of the Guide

(Swapan Mallick) (Dr. P. Goswami)